World Development 117 (2019) 172–182

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Tropical storms and mortality under climate change

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ARTICLE INFO

Article history:
Accepted 19 January 2019
Available online 31 January 2019

Keywords:
Tropical storms
Tropical cyclones
Hurricanes
Natural disasters
Human mortality
Human health
Climate change
Developing countries
Latin America
Mexico

ABSTRACT

Extreme weather induced by climate change can have major consequences for human health. In this study, I quantify the effect of tropical storm frequency and severity on mortality using objective meteorological data and the universe of vital statistics records from a large developing country, Mexico. Using a measure of storm exposure that accounts for both windspeed dispersion and population density along the storm track, I project changes in past storm-related mortality under various scenarios of continued climate change, while holding population and income at contemporaneous levels. I find that storm-related deaths would have risen under most climate change scenarios considered, with increases of as much as 52% or declines of as much as 10%, depending on the interplay between increasing storm severity and decreased frequency.

1. Introduction

Weather exerts a tremendous influence on human health. Extreme temperatures lead to excess mortality (Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2013; Deschenes & Moretti, 2009; Huang et al., 2011; Huynen, Martens, Schram, Weijenberg, & Kunst, 2001), influence long-term health (Deschenes, 2014; Compeán, 2013), and alter economies (Dell, Jones, & Olken, 2014, 2009, 2012). Weather-related natural disasters, including droughts, windstorms, and floods, killed more than 1.7 million people from 1970 to 2002 (Guha-Sapir, Below, & Hoyois, 2014). The death toll from natural disasters can be most severe in developing countries, where physical infrastructure and institutions are weakest (Anbarci, Escaleras, & Register, 2005; Kahn, 2005; Kellenberg & Mushfiq Mobarak, 2011).

Tropical storms, a type of windstorm, have led to significant economic damages (Belasen & Polachek, 2008, 2009; Hsiang & Jina, 2014; Nordhaus, 2010; Strobl, 2011, 2012; Yang, 2008), migration (Kugler & Yuksel, 2008; McIntosh, 2008), changes in educational attainment (Bluedorn & Cascio, 2005), mortality (Anttila-Hughes & Solomon, 2013; Borden & Cutter, 2008; Centers for Disease Control, 2013; Combs, Quenemoen, Gibson Parrish, & Davis, 1999; Haque et al., 2012; Hendrickson & Vogt, 1996; Jonkman, Maaskant, Boyd, & Levitan, 2009; Sadowski & Sutter, 2005; Yeo & Blong, 2010; Zahran, Tavani, & Weiler, 2013), and other health effects (Banerjee, 2015; Bourque, Siegel, Kano, & Wood, 2006; Caldera, Palma, Penayo, & Kullgren, 2001; Fredrick et al., 2015; Goenjian et al., 2001; Sanders et al., 1999; Shultz, Russell, & Espinel, 2005). Hurricane Katrina, which struck the United States in 2005, and Hurricane Mitch, which struck Central America in 1998, demonstrated the destructive potential of storms. Katrina killed 1833 people and caused $125 billion in damage, while Mitch killed 18,820 people and caused $6 billion in damage (EM-DAT, 2018).

Climate change brings not only a secular rise in temperatures, but also changing patterns of natural hazards, including tropical storms. Increasing severity of storms in recent decades has been linked to climate change via increases in ocean surface temperatures (Elsner, Kossin, & Jagger, 2008; Emanuel, 2005; Knutson et al., 2010; Mann & Emanuel, 2006; Webster, Holland, Curry, & Chang, 2005). Attributing causation to this link is tenuous, however. One study of past storms in the Atlantic concluded, "[I]t is premature to conclude that human activities—and particularly greenhouse gas emissions that cause global warming—have already had a detectable impact on hurricane activity" (Geophysical Fluid Dynamics Laboratory, 2018). Nonetheless, climate models project storm intensity to increase under continued climate change, though with decreased frequency (Bender et al., 2010; Emanuel, 1987; Emanuel, Sundararajan, & Williams, 2008; Knutson et al., 2010; Knutson, Tuleya, & Kurihara, 1998; Lin, Emanuel, Oppenheimer, & Vanmarcke, 2012; Villarini, Vecchi, Knutson, Zhao, & Smith, 2011).

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https://doi.org/10.1016/j.worlddev.2019.01.009
0305-750X/

This study considers how storm patterns related to climate change affect mortality, the most basic measure of human health. I quantify the effect of tropical storm frequency and severity on mortality using objective meteorological data and the universe of vital statistics records from a large developing country, Mexico. I look for evidence of adaptation to the mortality effects of storms across regions and time periods that are likely to differ in adaptive behavior. I use estimates from past storms to project changes in storm-related mortality under various scenarios of continued climate change, while holding population and income at contemporaneous levels. When applying storm patterns projected under climate change to the estimation sample, I find that storm-related deaths could have risen or fallen, depending on the interplay between increasing storm severity, which increases deaths, and decreased frequency, which decreases deaths.[1] I project that storm-related mortality would have risen under most scenarios considered. The results suggest that it is important to incorporate climate change scenarios when preparing for disasters, particularly in developing countries.

This study builds upon and contributes to several strands of literature. First, I add to the stock of knowledge on the effects of climate change on human health (Haines & Patz, 2004; Haines, Sari Kovats, Campbell-Lendrum, & Corvalán, 2006; Kovats, Campbell-Lendrum, & Matthies, 2005; McMichael, Woodruff, & Hales, 2006; Patz, Campbell-Lendrum, Holloway, & Foley, 2005). Second, I draw on projections of changing storm patterns induced by climate change to assess its social consequences, as Mendelsohn, Emanuel, Chonabayashi, and Bakkensen (2012) and Dinan (2017) have done for storm-related economic damage. The present study relates most closely to McMichael, Campbell-Lendrum, Kovats, Edwards, Wilkinson, Wilson, Nicholls, Hales, Tanser, and Le Sueur (2004), Dasgupta, Laplante, Murray, and Wheeler (2009), and Lloyd, Sari Kovats, Chalabi, Brown, and Nicholls (2015), each of which project global mortality due to storm surges under climate change.[2] I build on their work in several ways. First, I use a continuous measure of storm exposure that accounts for both windspeed dispersion and population density along the storm track (Yang, 2008). Second, I take a comprehensive approach that uses data on all storms and deaths over a 22-year period, rather than subjective determinations of deaths from single storm episodes. Third, I use subnational variation in storm intensity from a single country, Mexico, allowing me to hold constant national-level institutional influences on public health. My focus on a developing country with high-quality data also balances the need for accurate estimates with broader relevance, as the effects of tropical storms under continued climate change will disproportionately affect the developing world.

The paper proceeds as follows. Section 2 describes the measure of tropical storm exposure and the mortality data. Section 3 presents main results on the effect of tropical storms on mortality. Section 4 explores whether residents adapt to storms in ways that reduce storm-related mortality, as such adaptation would represent an important response to changing storm patterns under climate change. Section 5 projects storm-related mortality under climate change. Section 6 concludes.

[1] Note that this approach projects future climate change onto past data. A more sophisticated approach would also project changes in population and economic activity under climate change, though at the cost of the additional uncertainty inherent in such projections. See Dinan (2017) for an example.

[2] Following the literature, I use the phrase "under climate change" to refer to future scenarios of continued climate change that differ in severity. The implicit counterfactual is past climate change, not an alternative future in which climate change fails to occur.

2. Storm exposure and mortality data

Tropical storms are storms that originate over tropical oceans and have sustained winds exceeding 33 knots (61 km per hour).[3] Tropical storms carry three related risks for property and human health. First, strong winds from storms can cause direct damage. Second, tropical storms can cause a storm surge, or a temporary rise in sea level due to wind-driven waves. Storm surges can be massive in the case of the strongest storms. For instance, the surge caused by the 1970 Bangladesh hurricane was reported to have reached 30 feet (9 m). Third, storms can be accompanied by heavy rainfall, which can cause flooding or landslides. I expect these risks to lead to excess mortality beyond that experienced in the absence of storms.

Measuring the effect of tropical storm severity on mortality presents challenges. For instance, using government and/or media reports of storm damage, even if available for all tropical storms in the sample period, would risk biasing the estimates. Specifically, reverse causation is likely to be a problem. If excess deaths due to a storm are large, disaster damages may be exaggerated to attract more government or international aid. This would lead the estimated effect of damage on mortality to be upward biased. Alternatively, areas with the greatest monetary damage might be the wealthiest and most capable of reducing excess death, leading to downward bias. To avoid these possibilities, I use objective meteorological data on storm windspeed to measure storm exposure.

I use windspeed data on tropical storms originating in the Atlantic and eastern North Pacific oceans (the regions relevant to Mexico), available from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center, a U.S. government agency. NOAA analyzes data from reconnaissance aircraft, ships, and satellites to create "best tracks" of individual storms: positions (latitude and longitude) of storm centers at 6-hourly intervals, combined with intensity information (windspeed and barometric pressure; Jarvinen, Neumann, & Davis, 1993; Davis, Brown, & Preston, 1984; Chu, Sampson, Levine, & Fukada, 2002). Complete records for both ocean regions are available since 1949. Fig. 1 maps storm best tracks making landfall in Mexico.

I use data on tropical storm exposure and mortality in all 31 Mexican states, plus Mexico City, for each month during 1990–2011 (I chose the starting period based on the availability of microdata on mortality). I create an index to measure storm severity by incorporating two elements, windspeed and population density (Yang, 2008). A storm index S for state j, month m, and year t with this property is:

$$S_{jmt} = \frac{\sum_i \sum_s x_{isjmt}}{N_{jmt}} \tag{1}$$

where x measures the exposure of person i to storm s in state j at month m and year t. The exposure measure is the square of the windspeed above the tropical storm windspeed threshold (33 knots), normalized by the maximum of this variable. Specifically, x_{isjmt} is:

$$x_{isjmt} = \frac{(w_{isjmt} - 33)^2}{(w^{MAX} - 33)^2} \tag{2}$$

where w_{isjmt} is the windspeed, in knots, to which an individual was exposed. w^{MAX} is the maximum observed windspeed in Mexico over the period for which complete data are available for all storms in the country (1949–2011). The functional form reflects common practice in climatology, which models pressure on structures as rising in the square of windspeed, rather than a linear term (Emanuel,

[3] I base much of the background description of tropical storms and corresponding index presented here on Yang (2008), which in turn draws on Smith (1992), Alexander (1993), and Bryant (2005).

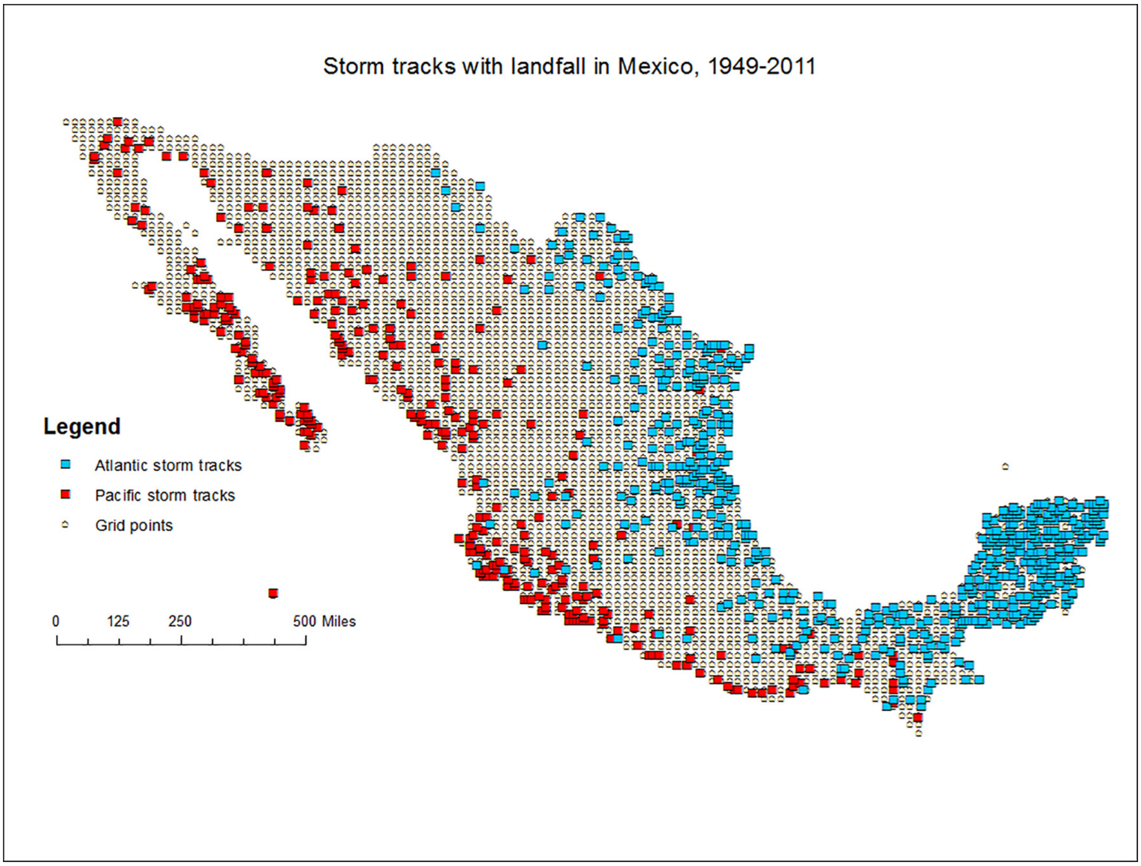

Fig. 1. Tropical storm landfall in Mexico, 1949–2011.

2005; Mahajan & Yang, 2017; Yang, 2008). I check for robustness to this assumption later in the paper.

Windspeed is observed directly only for points along the storm track, requiring me to estimate the windspeed exposure of individuals. Using a 0.25-degree-square national grid of Mexico, I follow Yang (2008) to estimate the windspeed experienced at each gridpoint. The procedure uses the storm best track data, a model of windspeed decay given distance from hurricane eyes (Dilley, 2005), and geographic information systems software. The procedure has three steps:

1. Predict the radius (in kilometers) of tropical storm-force winds using a regression equation incorporating windspeed along the storm track, latitude, and an indicator for whether the storm has made landfall:

$$\ln \widehat{radius}_s = -.616 + .475 \ln latitude_s + .056 \ln w_s + .848 \times \ln w_s^{max} - .118 land_s \quad (3)$$

where s indexes the point on the storm track, w is windspeed, and w_s^{max} is the maximum recorded windspeed throughout the best track. Use the predicted radii to determine which gridpoints experienced a tropical storm.

2. Find the distance between each affected gridpoint and the nearest point along the storm best track. Predict windspeed (in knots) at each gridpoint g associated with storm track point s as:

$$\widehat{w}_{gs} = 34 + (w_s - 34) \times \left[1 - \left(\frac{distance_{gs}}{\widehat{radius}_s}\right)\right] \quad (4)$$

3. Insert predicted windspeed into Eq. (2) to calculate the storm index for each affected gridpoint. Then sum across storms and gridpoints in the state-month-year cell. While there is no data source for individual-level hurricane exposure, I approximate it using data on population density. To capture population density along the storm track, I weight gridpoints by the population of the municipality in which it is located. I use municipal population from the 1990 Mexican Census; data from more recent Censuses might reflect population movements in response to storms within the sample and risk biasing the results. For municipalities with more than one gridpoint, I assume the population is uniformly distributed throughout the grid.

The storm index ranges from [0,1]. Its units are *intensity-weighted events per capita*. The index S_{jmt} would equal one if each of a state's residents were exposed to the maximum windspeed ($x_{isjmt} = 1$ for all residents) on a single occasion in a single month. State-month-years without any residents exposed to a tropical storm have a storm index of zero. This index improves upon other measures of storm severity based on meteorological data, such as the Saffir-Simpson scale (Categories 0–5), by measuring intensity continuously based on both storm strength and population exposure.

Mortality data are from the universe of Mexican Vital Statistics records. Beginning with 10.3 million individual recorded deaths, I

aggregate by state, month, and year. To construct mortality rates, I divide the deaths in each state-month-year cell by the population in that cell, using the Mexican Census from 1990, 2000, and 2010 and the Mexican Conteo (a large population survey conducted between Census years, comparable to the American Community Survey) from 1995 and 2005. I assume constant population growth to impute population values between surveys, and annualize monthly mortality rates by multiplying by 12.

Using the universe of all recorded deaths helps to avoid potential biases arising from official tallies of storm-related deaths, which may reflect desires to over- or under-report deaths for similar reasons as damage estimates. For instance, multiple independent research reports have suggested that the official government estimate of 64 deaths due to Hurricane Maria, which struck Puerto Rico in 2017, may represent just 1–6% of true excess mortality (Kishore et al., 2018; Robles, Davis, Fink, & Almukhtar, 2017). A limitation of using the universe of death records is the potential to attribute unrelated deaths to storms. Although information on cause of death could mitigate this concern, it is unclear which (if any) causes of death could be completely unrelated to storms, as any pre-existing condition could be exacerbated by storm exposure. For this reason, I use deaths due to all causes in estimation, but add a series of increasingly stringent controls to isolate the causal effect of storms. I also compare my estimates to those from sources that focus more narrowly on deaths attributed to disasters.

Fig. 2 shows the geographic distribution of storms during the sample period, with darker shading indicating greater storm frequency. As expected, coastal states experience more tropical storms than interior states. Fig. 3 shows the frequency and intensity of storms over time, revealing large fluctuations. I use this spatial and temporal variation in storm exposure to identify the effect of storms on mortality.

Table 1 shows summary statistics for the monthly state panel. Storms affect 217 of the 8448 state-months in the data, or 3 percent of the total. Conditional on a storm, the mean value of the storm index is 0.0077, with a standard deviation nearly three times as large, suggesting wide variation in storm severity. Almost all storms fall between Categories 1–3 on the Saffir-Simpson scale, though 7 percent of storms reach Category 4 (note that these categories are defined by state-month, rather than for an entire storm as in common usage). Mean mortality by state-month is 1215, with 56 percent of deaths by males, reflecting their lower life expectancy and the toll of drug-related violence during the sample period. Similarly, the male mortality rate of 5.3 per 1000 population is 37 percent greater than the female mortality rate. Mortality is more prevalent among the very young and old, with infants and those over 70 experiencing the highest mortality rates.

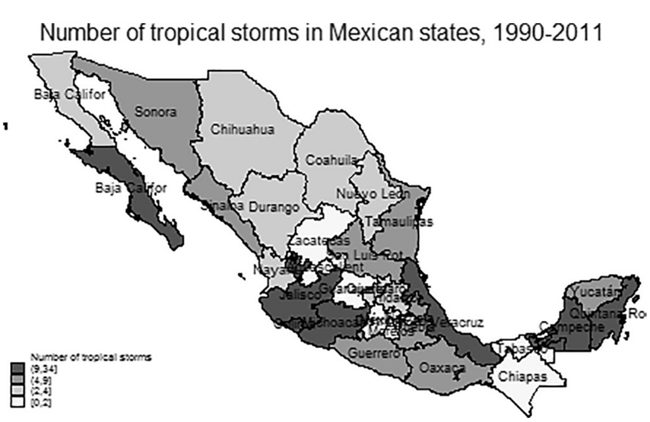

Fig. 2. Geographic distribution of tropical storms in Mexico, 1990–2011.

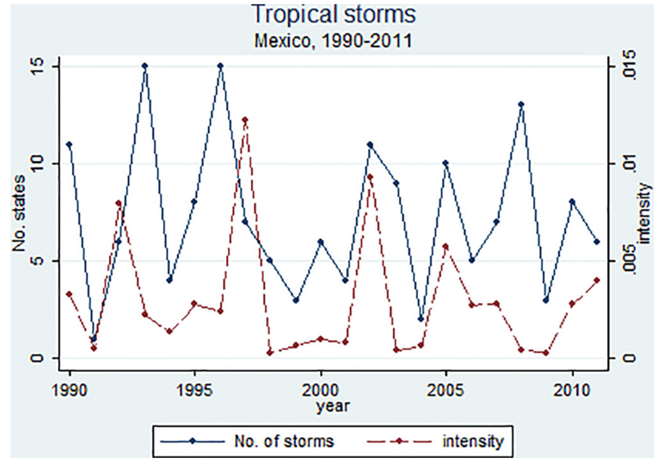

Fig. 3. Frequency and severity of tropical storms in Mexico, 1990–2011.

3. Effect of storms on mortality

3.1. Empirical specification

I identify the effect of storms on mortality using the regression equation:

$$MORT_{jmt} = \alpha + \beta S_{jmt} + \gamma_j + \delta_{mt} + \varepsilon_{jmt} \quad (5)$$

where j, m, and t are indices for state, month, and year; $MORT$ is mortality (level or rate); and S is the storm index. The state-specific fixed effects γ capture all time-invariant characteristics of a state that contribute to mortality, such as its geography, initial state of public health, and historical propensity to experience storms and other natural disasters. The time effects δ capture all characteristics common to all states in each month and year, such as national economic and political conditions, seasonal fluctuations, and climate change that occurs at national scale. The regression error term is ε. The coefficient of interest β therefore isolates excess deaths from storms, i.e., the effect of storms on mortality independent of any influences that are permanent within a state or common to all states within a particular month. I cluster standard errors by state, which accounts for arbitrary patterns of persistence in unobservable characteristics within a state over time.

3.2. Main results

Table 2 presents the main results. In column (1), the coefficient on the storm index means that a state experiencing the strongest possible storm ($S_{jmt} = 1$) is predicted to have 958.2 additional deaths in that month relative to a month without a storm.[4] This value is large relative to mean monthly mortality of 1215, and is statistically significant at 5%. The bottom of the table presents alternative ways to gauge the magnitude of a storm's effect on mortality. A storm of average strength (using the sample mean of the storm index, conditional on storm occurrence) would cause 7.4 additional deaths. A one standard deviation increase in storm intensity would lead to 20 additional deaths.

While these estimates may appear modest, it is important to note that they are for a single state; individual storms are likely to spread over several states. The estimates imply that storms killed 1598 people in Mexico from 1990 to 2011.[5] This figure

[4] The strongest storm observed during the sample period has an index of 0.153, for the state of Quintana Roo in October 2005. This observation reflects Hurricane Wilma, which was a Category 5 hurricane at its peak.

[5] The calculation uses the equation $\widehat{MORT} = \sum_j \sum_m \sum_t \hat{\beta} S_{jmt}$, where the circumflex denotes estimated values.

Table 1
Summary statistics.

Storms				Mortality		level		rate	
	N	mean	s.d.		N	mean	s.d.	mean	s.d.
storm index	8448	0.0002	0.004	total	8448	1215.1	1108.2	4.59	0.96
conditional on storm				male	8448	678.7	593.4	5.31	1.07
storm index	217	0.0077	0.021	female	8448	535.6	517.1	3.88	0.93
Saffir-Simpson scale				age group					
Category 0	217	1.00	0.00	under 1	8448	104.1	121.8	18.26	9.58
Category 1	217	0.21	0.41	1–4	8448	22.2	25.8	0.91	0.64
Category 2	217	0.07	0.25	5–14	8448	19.6	17.9	0.33	0.15
Category 3	217	0.03	0.16	15–29	8448	80.1	68.3	1.12	0.37
Category 4	217	0.005	0.07	30–49	8448	161.9	150.5	2.55	0.63
				50–69	8448	309.0	299.3	10.75	2.20
				70 or older	8448	512.6	477.5	57.58	12.29

Sample is monthly panel of Mexican states, 1990–2011. Saffir-Simpson scale variables are dummies for storm of indicated category or greater. Mortality rate is deaths per 1000 population, annualized.

Table 2
Effect of tropical storms on mortality.

	level			rate		
	overall (1)	male (2)	female (3)	overall (4)	male (5)	female (6)
storm index	958.2	444.8	512.5	3.12	3.49	2.75
	(436.0)**	(225.0)*	(215.9)**	(0.98)***	(0.98)***	(1.23)**
N	8448	8448	8448	8448	8448	8448
R-squared	0.54	0.51	0.54	0.54	0.51	0.49
mean outcome	1215.1	535.6	678.7	4.59	3.88	5.31
effect of average storm	7.4**	3.4**	3.9**	0.02***	0.03***	0.02**
	(3.4)	(1.7)	(1.7)	(0.01)	(0.01)	(0.01)
marginal effect of storm	20.0**	9.3**	10.7**	0.07***	0.07***	0.06**
	(9.1)	(4.7)	(4.5)	(0.02)	(0.02)	(0.03)

Sample is monthly panel of Mexican states, 1990–2011. All regressions include state and month-by-year fixed effects. Mortality rate is deaths per 1000 population, annualized. Standard errors clustered by state. Effect of average storm = coefficient on storm index × mean (storm index|storm index >0). Marginal effect of storm = coefficient(s) on storm index × s.d. (storm index|storm index >0). * significant at 10%; ** significant at 5%; *** significant at 1%.

exceeds the 989 deaths attributed to tropical storms in Mexico over the same period according to the International Disaster Database, the most comprehensive source for disaster data (EM-DAT, 2018). The discrepancy may be due to the different methodologies used. The Database is restricted to events with at least 10 deaths, 100 people affected, or for which there was a declaration of a state of emergency or call for international assistance. It relies on reports from the United Nations, governments, aid organizations, insurance companies, and the press. It may therefore reflect only "direct" deaths immediately attributable to larger storms, omitting smaller storms or any additional "indirect" deaths due to pre-existing health conditions exacerbated by storm exposure.

Columns (2)–(3) present results for male and female mortality levels separately. The storm coefficient for females is larger in magnitude and more precisely estimated than for males.

Column (4) shows that the strongest possible storm would raise the mortality rate by 3.12 deaths per thousand population, an increase of 68% over the baseline, and significant at the 1% level. A storm of average strength raises the mortality rate by 0.02 per thousand, while a one standard deviation increase in storm intensity would increase the mortality rate by 0.07.

Looking separately at male and female mortality rates in columns (5)-(6) reveals that the storm coefficient for males is larger in magnitude and more precisely estimated than for females, the opposite pattern observed for the mortality level. The discrepancy reflects Mexico's lower male population due to international migration and drug-related violence. Higher storm-related mortality rates for men may reflect several factors. Men may be more likely than women to be exposed to the most destructive aspects of storms as emergency personnel (e.g., fire, law enforcement, emergency medical technicians, or construction and maintenance workers). The health of older men may also be less robust to storm-related stresses on existing medical conditions, consistent with lower male life expectancy.

Table 3 presents results by age group, with mortality level as the dependent variable in Panel A and mortality rate in Panel B. Column (1) recapitulates the results from Table 2 for reference. In Panel A, I find that the age groups with the largest number of deaths are infants (under 1) and older adults (50 and above), though it is not clear from these results whether these magnitudes are due to greater vulnerability of these groups or higher prevalence in the population. Panel B accounts for population prevalence by using age-specific mortality rates, showing that infants and the elderly (70 and above) are most vulnerable to storms. The strongest storm would increase infant mortality by 25.5 per thousand, or 1.4 times the mean, and is statistically significant at 10%. For the elderly, the storm coefficient is about the same magnitude as the mean mortality rate, and also significant at 10%. These results show that the young and old are most vulnerable to storm-induced mortality.

3.3. Robustness checks

Table 4 alters the regressions for the overall mortality level to probe robustness of results. Column (1) includes the main result from Table 2 for reference. Columns (2)–(3) of Table 4 allow the storm's effects to persist for one or two additional months after it makes landfall by including the first and second monthly lags of the storm index, $S_{jm,t-1}$ and $S_{jm,t-2}$. The coefficients on these lagged values of the storm index are not significant.

Table 3
Effect of tropical storms on mortality, by age group.

	total	under 1	1–4 yrs	5–14 yrs	15–29 yrs	30–49 yrs	50–69 yrs	70 or older
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: level								
storm index	958.2	144.9	49.5	21.1	63.4	106.7	172.4	391.6
	(436.0)**	(111.9)	(35.4)	(13.1)	(32.7)*	(38.4)***	(152.6)	(400.6)
N	8448	8448	8448	8448	8448	8448	8448	8448
R-squared	0.54	0.34	0.35	0.23	0.18	0.42	0.53	0.55
mean outcome	1215.1	104.1	22.2	19.6	80.1	161.9	309.0	512.6
effect of average storm	7.4**	1.1	0.4	0.2	0.5*	0.8***	1.3	3.0
	(3.4)	(0.9)	(0.3)	(0.1)	(0.3)	(0.3)	(1.2)	(3.1)
marginal effect of storm	20.0**	3.0	1.0	0.4	1.3*	2.2***	3.6	8.2
	(9.1)	(2.3)	(0.7)	(0.3)	(0.7)	(0.8)	(3.2)	(8.4)
Panel B: rate								
storm index	3.12	25.54	2.72	−0.07	−0.34	1.65	5.93	57.04
	(0.98)***	(13.45)*	(1.72)	(0.29)	(1.04)	(1.76)	(3.28)*	(29.56)*
N	8,448	8,448	8,448	8,448	8,448	8,448	8,448	8,448
R-squared	0.54	0.56	0.45	0.22	0.16	0.25	0.47	0.59
mean outcome	4.59	18.26	0.91	0.33	1.12	2.55	10.75	57.58
effect of average storm	0.02***	0.20*	0.02	−0.001	−0.003	0.01	0.05*	0.44*
	(0.01)	(0.10)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.23)
marginal effect of storm	0.07***	0.53*	0.06	−0.001	−0.007	0.03	0.12*	1.19*
	(0.02)	(0.28)	(0.04)	(0.01)	(0.02)	(0.04)	(0.07)	(0.62)

Sample is monthly panel of Mexican states, 1990–2011. All regressions include state and month-by-year fixed effects. Mortality rate is deaths per 1000 population, annualized. Standard errors clustered by state. Effect of average storm = coefficient on storm index × mean (storm index|storm index >0). Marginal effect of storm = coefficient(s) on storm index × s.d. (storm index|storm index >0). * significant at 10%; ** significant at 5%; *** significant at 1%.

Columns (4)–(6) check the robustness of the estimates by allowing mortality to vary flexibly within states over time. These specifications are important to ensure that idiosyncratic factors within a state, such as economic growth that is particularly slow or fast relative to the national average, or drug cartel-related violence, are not spuriously correlated with the prevalence of storms and therefore biasing the estimates. Column (4) includes state-specific linear time trends in mortality, while column (5) adds a state-specific quadratic trend. Column (6) includes state-by-year effects, which account for all factors common to a state within a year, such as annual economic growth or changes in political representation. In this specification, the effect of storms on mortality reflects deviations from a state's mean monthly mortality within a particular year.[6] The effect of storms on mortality is of similar magnitude and precision as the baseline estimate across each of these stringent specifications.

The squared terms in the storm index emphasize storms with the strongest windspeeds. If the effect of storms on mortality is instead linear in windspeed, the index would be misspecified, biasing the estimates. To explore this possibility, column (7) of Table 4 shows results when removing the squared terms from Eq. (2) when calculating the storm index.[7] The coefficient on the storm index is positive and significant at 1%. The estimate implies that an average storm kills 14 people, nearly double the estimate of 7.4 deaths when using the original storm index. A one standard deviation increase in storm intensity would lead to 25 additional deaths, compared to 20 for the original storm index. Both versions of the index fit the data equally well, with identical R-squared values of 0.54. In sum, the linear and squared storm indices produce results that are consistent with each other. However, the squared storm index produces estimates that are more conservative.

Another potential source of misspecification in the main results is the weighting of storm-affected gridpoints by 1990 municipal population. An alternative approach is to weight all gridpoints within a state equally, while including lagged population as an additional explanatory variable. Column (8) of Table 4 presents results. The coefficient on this unweighted storm index is positive and significant. The implied average and marginal effects reported at the bottom of the table are similar in magnitude to those in the baseline model.

A final source of potential misspecification that I explore is to include state income in the model, as a state's level of economic development can moderate the effect of storms on mortality. I excluded income from the baseline model because the first year of state gross domestic product publicly reported by INEGI, the Mexican statistics agency, is 2003, which would reduce the sample size by more than half. Additionally, the inclusion of state-by-year effects in column (6) accounts for annual state income without sacrificing observations. Nonetheless, for completeness I report results when including the natural log of annual state income per capita (lagged one year) for the available years in Table 4, column (9). The coefficient on the storm index is positive and significant. The implied average and marginal effects reported at the bottom of the table are similar in magnitude to those in the baseline model.

Table 5 presents results for the mortality rate using the same methods as Table 4. The results mirror the findings of Table 4. The storm effect on mortality fails to persist beyond the month of landfall. Estimates are highly robust to the inclusion of state-specific mortality trends, different specifications of the storm index, and to the inclusion of state income per capita.

4. Adaptation in response to tropical storms

Households and institutions may adapt to the likelihood of tropical storms by taking actions that reduce storm-related mortality. These adaptations could reduce the contemporaneous effect of storms on mortality and make residents more likely to survive

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[6] More formally, columns (4)–(6) of Tables 4 and 5 add state-specific effects $f_s(m,t)$ that vary over time:

$$MORT_{jmt} = \alpha + \beta S_{jmt} + \gamma_s + \delta_{mt} + f_s(m,t) + \varepsilon_{jmt}$$

Let τ be a variable that is linear in months during the sample period, so that $\tau = 1$ corresponds to January 1990, $\tau = 2$ is February 1990, etc. Then $f_s(m,t)$ is specified in Tables 4 and 5 as:
Column (4), linear state trends: $f_s(m,t) = \theta_s\tau$
Column (5), quadratic state trends: $f_s(m,t) = \theta_{1s}\tau + \theta_{2s}\tau^2$
Column (6), state-by-year fixed effects: $f_s(m,t) = \theta_{st}$

[7] In other words, I re-specify Eq. (2) as $\frac{W_{isjmt}-33}{W^{MAX}-33}$.

Table 4
Effect of tropical storms on mortality (level).

	mortality (level)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
storm index(t)	958.2 (436.0)**	958.9 (436.8)**	953.1 (440.9)**	1041.8 (243.0)***	967.9 (224.0)***	898.8 (232.4)***	498.7 (169.1)***	3343.5 (1,057.7)***	1041.8 (267.9)***
storm index(t-1)		294.5 (414.3)	293.1 (414.6)						
storm index(t-2)			−621.0 (598.1)						
N	8448	8448	8448	8448	8448	8448	8448	8416	3072
R^2	0.54	0.54	0.54	0.71	0.73	0.74	0.54	0.63	0.51
mean outcome	1215.1	1215.1	1215.1	1215.1	1215.1	1215.1	1215.1	1214.3	1382.9
effect of average storm	7.4** (3.4)	7.4** (3.4)	7.3** (3.4)	8.0*** (1.9)	7.4*** (1.7)	6.9*** (1.8)	14.0*** (4.7)	8.7*** (2.8)	8.0*** (2.1)
marginal effect of storm	20.0** (9.1)	20.0** (9.1)	19.9** (9.2)	21.7*** (5.1)	20.2*** (4.7)	18.7*** (4.8)	25.5*** (8.7)	25.0*** (7.9)	21.7*** (5.6)
state-specific linear trend				x	x				
state-specific quadratic trend					x				
state × year fixed effects						x			
linear storm index							x		
unweighted storm index								x	
includes income per capita									x

Sample is monthly panel of Mexican states, 1990–2011. All regressions include state and month-by-year fixed effects. Regressions using unweighted storm index also include lagged population as explanatory variable. Standard errors clustered by state. Effect of average storm = coefficient on storm index × mean (storm index|storm index >0). Marginal effect of storm = coefficient(s) on storm index × s.d. (storm index|storm index >0). Income per capita is natural log of state GDP per capita, lagged one year, in constant 2013 pesos. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5
Effect of tropical storms on mortality rate.

	mortality rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
storm index(t)	3.12 (0.98)***	3.12 (0.98)***	3.13 (0.97)***	2.96 (1.13)**	2.90 (1.18)**	2.60 (1.04)**	2.03 (0.36)***	8.99 (3.41)**	2.29 (0.64)***
storm index(t-1)		0.88 (0.68)	0.88 (0.67)						
storm index(t-2)			0.46 (1.52)						
N	8448	8448	8448	8448	8448	8448	8448	8416	3072
R^2	0.54	0.54	0.54	0.66	0.68	0.71	0.55	0.55	0.60
mean outcome	4.59	4.59	4.59	4.59	4.59	4.59	4.59	4.58	4.78
effect of average storm	0.02*** (0.01)	0.02*** (0.01)	0.02*** (0.01)	0.02*** (0.01)	0.02** (0.01)	0.02** (0.01)	0.06*** (0.01)	0.02*** (0.01)	0.02*** (0.00)
marginal effect of storm	0.07*** (0.02)	0.07*** (0.02)	0.07*** (0.02)	0.06*** (0.02)	0.06** (0.02)	0.05** (0.02)	0.10*** (0.02)	0.07*** (0.03)	0.05*** (0.01)
state-specific linear trend				x	x				
state-specific quadratic trend					x				
state × year fixed effects						x			
linear storm index							x		
unweighted storm index								x	
includes income per capita									x

Sample is monthly panel of Mexican states, 1990–2011. All regressions include state and month-by-year fixed effects. Regressions using unweighted storm index also include lagged population as explanatory variable. Mortality rate is deaths per 1000 population, annualized. Saffir-Simpson scale variables are dummies for storm of indicated category or greater. Standard errors clustered by state. Effect of average storm = coefficient on storm index × mean (storm index|storm index >0). Marginal effect of storm = coefficient(s) on storm index × s.d. (storm index|storm index >0). Income per capita is natural log of state GDP per capita, lagged one year, in constant 2013 pesos. * significant at 10%; ** significant at 5%; *** significant at 1%.

future storms. Successful adaptation could thus prepare residents to face the changing patterns of storms predicted under climate change.

I look for evidence of adaptation by comparing regions and time periods that are likely to differ in their adaptive behavior in response to storms. Conditional on storm severity, I expect that states with greater prior exposure to tropical storms should experience lower storm-related mortality because of adaptation. I also expect that storm-related mortality should decline over time as successful strategies to prepare for tropical storms take hold. These responses represent only a few of the many possible forms of adaptation, of course. They serve as a useful starting point, not the final word. In particular, increases in income over longer time spans than those considered here should bring many forms of useful adaptation, as richer societies can deploy additional resources to prevent storm-related deaths.

To test for adaptation, I regress mortality on the storm index and its interaction with measures of storm exposure prior to the sample period. I continue to include state and year-by-month effects in all regressions. In Table 6, column (1), I define storm exposure as an indicator for the state experiencing past storms (1949–1989) at above-median frequency. As expected, the coefficient on this interaction term is negative for both the mortality level (Panel A) and rate (Panel B), consistent with an adaptive

Table 6
Adaptation in response to tropical storms.

	full sample			1990–2000	2001–2011
	(1)	(2)	(3)	(4)	(5)
Panel A: mortality level					
storm index	13967.2	382.7	4759.4	1100.2	1094.3
	(8661.5)	(364.2)	(7642.4)	(326.9)***	(297.7)***
storm index interacted with:					
historical storm frequency above median	−13017.0				
	(8584.8)				
historical storm severity above median		833.7			
		(701.1)			
coastal state			−3805.9		
			(7639.8)		
Observations	8448	8448	8448	4224	4224
R-squared	0.54	0.54	0.54	0.44	0.53
Mean outcome	1215.1	1215.1	1215.1	1100.9	1329.2
storm coefficient + interaction	950.2**	1216.4**	953.5**		
	(432.9)	(618.4)	(434.7)		
Panel B: mortality rate					
storm index	12.77	4.06	−12.79	2.11	3.12
	(30.04)	(0.79)***	(25.04)	(2.68)	(0.87)***
storm index interacted with:					
historical storm frequency above median	−9.66				
	(29.92)				
historical storm severity above median		−1.35			
		(1.37)			
coastal state			15.93		
			(24.87)		
Observations	8448	8448	8448	4224	4224
R-squared	0.54	0.54	0.54	0.55	0.62
Mean outcome	4.59	4.59	4.59	4.49	4.68
storm coefficient + interaction	3.12***	2.70**	3.14***		
	(0.97)	(1.14)	(0.98)		

Sample is monthly panel of Mexican states, 1990–2011. All regressions include state and month-by-year fixed effects. Mortality rate is deaths per 1000 population, annualized. All interaction terms are dummies for state being above median for given characteristic. Historical storm frequency is number of months with tropical storm, 1949–1989. Historical storm severity is average value of storm index, conditional on storm, 1949–1989. Standard errors clustered by state. * significant at 10%; ** significant at 5%; *** significant at 1%.

response to prior storm exposure. However, neither interaction term is statistically significantly different from zero, meaning that I cannot reject equal mortality between states with high or low frequency of prior storm exposure.

In column (2) I redefine prior storm exposure as an indicator for above-median average storm severity (conditional on a storm).[8] Here again the coefficients on the interaction terms are not statistically significant, with opposite signs according to whether the outcome is the mortality level or rate. In column (3) I interact the storm index with an indicator for coastal state, where storms are more likely to strike (Figs. 1 and 2). Again, the interaction coefficients are insignificant and flip signs.[9] Interestingly, the sum of the storm index main effect plus interaction (bottom of table), representing the storm effect in states where the interaction term is non-zero, are statistically significant and similar in magnitude to the main effects reported in Table 2. These results suggest that the main estimates of storm-related mortality are driven by areas with the greatest storm exposure, where I would expect adaptation to be strongest.

I also test whether storm-related mortality changes over time by splitting the sample into early (1990–2000) and later (2001–2011) periods. The storm index coefficients are nearly identical between the two periods when the outcome is the mortality level (Table 6, Panel A, columns 4–5), with a larger point estimate for the later period when analyzing the mortality rate (Panel B). Moreover, only the later-period coefficients are statistically significant. These results are contrary to what I would expect if there were adaptation over time to the mortality effects of tropical storms. Overall, I find little evidence of storm-related adaptation in the data.[10] These results should give greater confidence in projections of storm-related mortality under climate change, to which I now turn.

5. Mortality projections under climate change

I use the estimates of the effect of storms on mortality to project storm-related mortality under continued climate change. As climate change proceeds, storms are likely to become more severe but less frequent (Bender et al., 2010; Emanuel et al., 2008; Emanuel, 1987; Knutson et al., 1998, 2010; Lin et al., 2012; Villarini et al., 2011). Because I observe past storm frequency and severity in the data, I can predict how many storm-related deaths would have occurred under alternate storm patterns during the sample period. I calculate counterfactual storm indices under climate change by altering the observed storm index along two dimensions: 1) intensity and 2) frequency. On intensity, I simulate windspeed increases of 5% and 10%, consistent with projected increases in storm intensity reported in the literature (Knutson et al., 1998, 2010). To do so, I increase predicted windspeed at each gridpoint along the storm track by these amounts and recalculate

[8] For this measure of prior storm severity, I weight all gridpoints equally rather than by 1990 municipal population in order to prevent endogenous population flows in response to storms from biasing the index. Changing municipal boundaries would make it problematic to weight by municipal population prior to the start of the storm index in 1949.

[9] I also fail to find evidence that wealthier states adapt better to storms. Interacting the storm index with a dummy for state GDP above median (based on predetermined GDP from 1988) also produces insignificant coefficients. Results not shown but available upon request.

[10] I find similar results when including state-by-year effects. Results omitted for brevity but available from the author upon request.

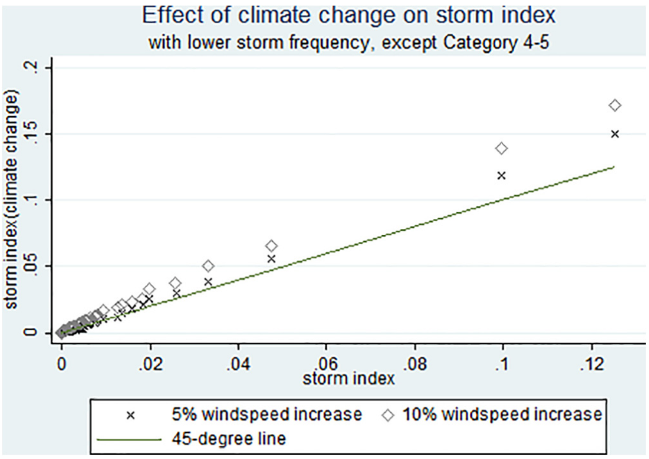

Fig. 4. Effect of climate change on storm index.

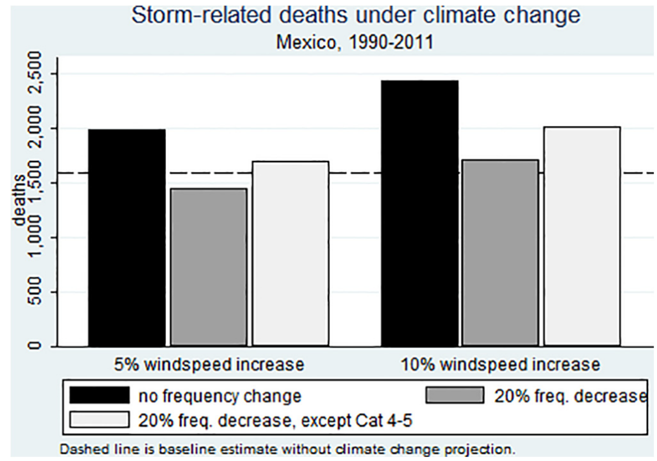

Fig. 5. Storm-related deaths under climate change.

the storm index. This will not alter the storm index in a mechanical way, because the storm index depends on the non-linearity of its functional form, the number of gridpoints exposed to a storm within a state, and the population density along the storm track.

I simulate reduced storm frequency by dropping a randomly selected 20% of positive values of the storm index, consistent with the midrange of projected frequency decreases (Knutson et al., 2010). I also alter this scenario in some simulations by retaining any storms that reach Category 4 or 5 on the Saffir-Simpson scale (Webster et al., 2005).

Fig. 4 shows how increased storm severity and decreased frequency alters the values of the storm index. Each point in the Q-Q plot represents a quantile of the distribution, with the observed storm index on the horizontal axis and the projected storm index under climate change on the vertical axis. Points above the 45-degree line indicate a projected increase in storm severity relative to observed values. Most points in the figure lie above this line, with increasing disparities in the highest quantiles (strongest storms).

Using these counterfactual storm indices, I predict storm-related deaths by multiplying the baseline estimate (the storm index coefficient in Table 2, column [1]) by the simulated values of the storm index, then summing over all states and time periods:

$$\widetilde{MORT} = \sum_{j} \sum_{m} \sum_{t} \hat{\beta} \tilde{S}_{jmt} \quad (4)$$

where $\widetilde{MORT}$ is predicted mortality under the climate change scenario; $\hat{\beta} = 958.2$ is the baseline estimate of the storm effect; S is the storm index under the climate change scenario; and j, m, and t are indices for state, month, and year as before.

Fig. 5 shows how the change in storm patterns under continued climate change affects mortality. Each bar shows predictions of storm-related deaths during the sample period under different climate change scenarios, with the dashed line representing baseline (no adjustment) estimates. Whether continued climate change increases or decreases mortality relative to this baseline depends on the interplay between increased storm severity and reduced frequency; although stronger storms kill more people, their reduced frequency will kill fewer over a given time period. At one extreme, a windspeed increase of 10% without any change in storm frequency would have killed 832 more people in Mexico from 1990 to 2011. However, a windspeed increase of 5% coupled with 20% lower frequency would have killed 153 fewer people. In proportional terms, these projections range from a 52% increase in storm-related deaths to a 10% decrease. Other scenarios fall between these extremes, but the latter is the only case under which deaths would fall among the scenarios considered.[11]

6. Conclusion

Changing patterns of extreme weather under continued climate change will have major consequences for human health. I find that past storm-related deaths in Mexico would have differed dramatically under projected climate change, with increases of as much as 52% or decreases of as much as 10%, depending on the interplay between increased storm intensity and decreased frequency. These findings are an important step in connecting the changes in natural hazards predicted under continued climate change to their human consequences.

All exercises in prediction are fraught with difficulty, and this study is no exception. First is the inherent uncertainty in climate science, a limitation of all studies projecting the consequences of climate change. A second limitation is the possibility that societies will take actions, beyond those already in place during the sample period, to mitigate the human costs of storms, as found in an emerging literature on adaptation to storm exposure (Bakkensen & Mendelsohn, 2016; Hsiang & Narita, 2012; Seo & Bakkensen, 2016). Although I find little empirical evidence of past adaptation to storm-related mortality, I of course cannot rule out its occurrence. Additionally, the role that changes in population and income might play in future storm-related mortality do not enter the model of this study.

An important form of adaptation not addressed in this study is evacuations. Public officials may order residents to evacuate in response to impending storms, potentially saving many lives. I lack data on evacuations, however, preventing me from estimating their effect on storm-related mortality. All estimates in the paper are therefore inclusive of any evacuations ordered during the sample period. Accurate forecasting of incoming storm tracks, combined with judicious use of evacuations by policymakers, could help to mitigate deaths caused by future storms under climate change. These and other forms of adaptation may in turn alter the future effects of storms in ways unforeseen by the model.

[11] To check robustness, I repeat these simulations using results from the model with state-by-year fixed effects (Table 4, column 6), which produces a more conservative estimate of storm impact. These simulations imply that storms killed 1499 people in Mexico during the sample period, similar to the baseline estimate of 1598. An increase of 10% in storm windspeed without any change in storm frequency would have killed 781 more people during the sample period under this revised simulation. An increase of 5% in windspeed coupled with a 20% reduction in severity would have killed 14 fewer people. These results are comparable to the range of +832 to −153 under the simulations from the baseline model.

Conflict of interest statement

I declare that I have no conflict of interest related to this submission.

Acknowledgements

I am grateful to Dean Yang for sharing programs for constructing the storm index used in this paper. HwaJung Choi, Alexandra Giza, Justin Ladner, and Roberta Nilson provided excellent research assistance.

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